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STRUCTURE PRESERVING TRANSFORMATIONS IN THE COMPARISON

OF COMPLEX STEADY-STATE SOUNDS

James H. Howard, Jr., and Donald C. Burgy

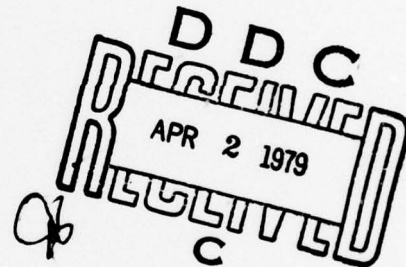ONR CONTRACT NUMBER N00014-75-C-0308

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20. ABSTRACT (Continue on reverse side if necessary and identify by block number) A process-oriented feature selection model was proposed to characterize listeners' comparisons of complex sounds. Specifically, the model assumes that the listener performs a structural analysis on the low-resolution spectra of the stimuli to be compared and then extracts a feature representation through a structure-preserving transformation resembling a principal-components analysis. This feature representation is subsequently employed to make similarity judgments between stimuli. Predictions of the model for a timbre-comparison task were examined using a set of sixteen→

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complex sounds that varied in amplitude-spectral shape. The subjective feature representation obtained from the ALSCAL nonmetric scaling program was generally consistent with the theoretical feature representation produced by the optimal structure-preserving transformation applied to the loudness-weighted spectra. The two comparison features as well as the relative importance of the two dimensions were successfully predicted by the model. Practical implications for the subjective evaluation of complex signals are discussed and refinements to the transformations in the model are suggested for further research.

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A variety of recent auditory psychophysical studies have required listeners to evaluate the subjective similarity of two or more complex acoustic stimuli. Such studies have involved both speech (Shepard, 1972) and complex nonspeech sounds (Miller & Carterette, 1975; Howard, 1977; Grey & Gordon, 1978). It is generally assumed that the similarity ratings obtained in this situation reflect the outcome of a peceptual comparison based on one or more psychophysical features that characterize members of the stimulus set. Typically, standard metric and nonmetric multidimensional scaling techniques are used to extract a set of perceptual dimensions from the observed matrix of similarity judgments. The dimensions revealed in this analysis are thought to reflect the elementary perceptual units or features that the listeners used to compare the stimuli. An important implicit assumption in this research is that human listeners can reliably report the perceived similarity among sounds even though they may not be explicitly aware of the underlying stimulus features. As Plomp and his associates have indicated (Plomp, 1976), these methods have contributed significantly to our understanding of the processes involved in timbre perception.

## The Feature Selection Problem

The specific question addressed in the present paper concerns the perceptual features listeners use to make pairwise similarity judgments on a set of sixteen complex steady-state sounds that differ primarily in timbre. How are the elementary units of comparison determined? What criteria do listeners use to select a subset of all possible dimensions for comparing the

individual members of the stimulus set?

Howard and Ballas (1978) have referred to this as the feature selection problem. Two contrasting approaches to this problem have been suggested in the literature. First, the human auditory system may be equipped with a set of specific feature detecting mechanisms that monitor incoming aural information for particular stimulus cues (e.g., Barlow, 1972). This approach emphasizes the importance of the feature detectors themselves. Each detector "looks for" an individual stimulus property, and a set of feature detectors determines a property list for the stimulus. Howard and Ballas (1978) referred to this as the property-list approach. Second, it is possible that the auditory system has an internalized set of rules and criteria for feature selection rather than a set of finely-tuned feature detectors. These rules and processes enable the listener to determine what the comparison features should be in any particular stimulus context. This view was called the process-oriented approach (Howard & Ballas, 1978).

Although evidence supporting both positions can be found in the literature, Howard and Ballas (1978) argue that the process-oriented approach is more naturally suited for theorizing about the timbre comparison task. While it may be reasonable to argue that man has evolved specialized brain "filters" for certain aural cues (e.g., speech features), an extension of this argument to include detectors for the individual timbre attributes of complex tones resists credibility. Since timbre obviously encompases a large set of

perceptual attributes (Plomp, 1976;  von Bismarck, 1974), at the
very least, a property-list approach to timbre comparison  would
suffer  an  embarrasing  lack  of parsimony.  Furthermore, if we
were to argue that only a subset of detectors would be  used  in
any particular comparison task then we would still be obliged to
explain  how  that  subset  is  selected  by  the  listener.
Consequently,  in  the present paper we adopt a process-oriented
approach to the feature  selection  problem.   In  other  words,
rather  than searching for the set of invariant auditory feature
detectors that underlie timbre comparison, we  will  attempt  to
outline  some  general principles that would account for feature
selection in a variety of comparison contexts.

## Toward a Model of Feature Selection

In their recent  treatment  of  this  problem,  Howard  and
Ballas  (1978) argue  that  when asked to compare the timbre of
steady-state  sounds,  human  listeners  perform  a  structural
analysis  on  the  low-resolution  spectra  of  the  comparison
stimuli.  In this case, the feature  selection  process  may  be
thought  of  as  a structure preserving transformation that maps
stimuli  from  an  initial  low-level  representation  (the
measurement  representation)  onto a higher-order representation
of lower dimensionality (a feature representation).  In the case
of  steady-state  complex  sounds  it  may  be  argued  that the
measurement  representation  is  approximated  by  a  1/3-octave
spectral  analysis,  adjusted for unequal sensitivity across the
spectrum (Zwicker,  Flottorp  &  Stevens,  1957).   Although  in
general  it is evident that information will be lost with such a

transformation, Howard and Ballas (1978) argue that listeners select the comparison features so as to minimize this loss. In other words, in a comparison task, features are selected to account for as much of the variability among the measurement representations of the stimuli as possible. They point out that a transformation having these properties is very similar to a principal components analysis.

A principal components analysis provides a transformation that maps objects from one space into a subspace of lower dimensionality. The first principal component is simply a new axis in the original space that accounts for most of the variability among the objects. In other words, the set of projections of objects in the measurement space onto the first principal component has maximum variance. The second principal component is an axis orthogonal to the first that accounts for most of the residual variance and so on (Harris, 1975).

Given these arguments, we can construct a preliminary model of the stimulus comparison process for steady-state complex sounds. Figure 1 displays an outline of our approach.

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Insert Figure 1 here

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An initial measurement transformation, denoted $M$, determines a measurement representation from the time-domain stimuli.[1] We assume that $M$ reflects a low-resolution spectral analysis, and denote the measurement representation for stimulus $S_i$ by a column vector of m 1/3-octave band levels, $\underline{x}_i = M(S_i)$, where

SIMILARITY JUDGMENT

$$C\left(\underline{F}_i, \underline{F}_j\right)$$

$C$

FEATURE REPRESENTATION

$$\underline{F}_1 = \begin{pmatrix} F_{11} \\ F_{12} \\ \vdots \\ F_{1n} \end{pmatrix} \quad \underline{F}_2 = \begin{pmatrix} F_{21} \\ F_{22} \\ \vdots \\ F_{2n} \end{pmatrix} \quad \cdots \quad \underline{F}_N = \begin{pmatrix} F_{N1} \\ F_{N2} \\ \vdots \\ F_{Nn} \end{pmatrix}$$

$T$

MEASUREMENT REPRESENTATION

$$\underline{X}_1 = \begin{pmatrix} X_{11} \\ X_{12} \\ \vdots \\ X_{1m} \end{pmatrix} \quad \underline{X}_2 = \begin{pmatrix} X_{21} \\ X_{22} \\ \vdots \\ X_{2m} \end{pmatrix} \quad \cdots \quad \underline{X}_N = \begin{pmatrix} X_{N1} \\ X_{N2} \\ \vdots \\ X_{Nm} \end{pmatrix}$$

$M$

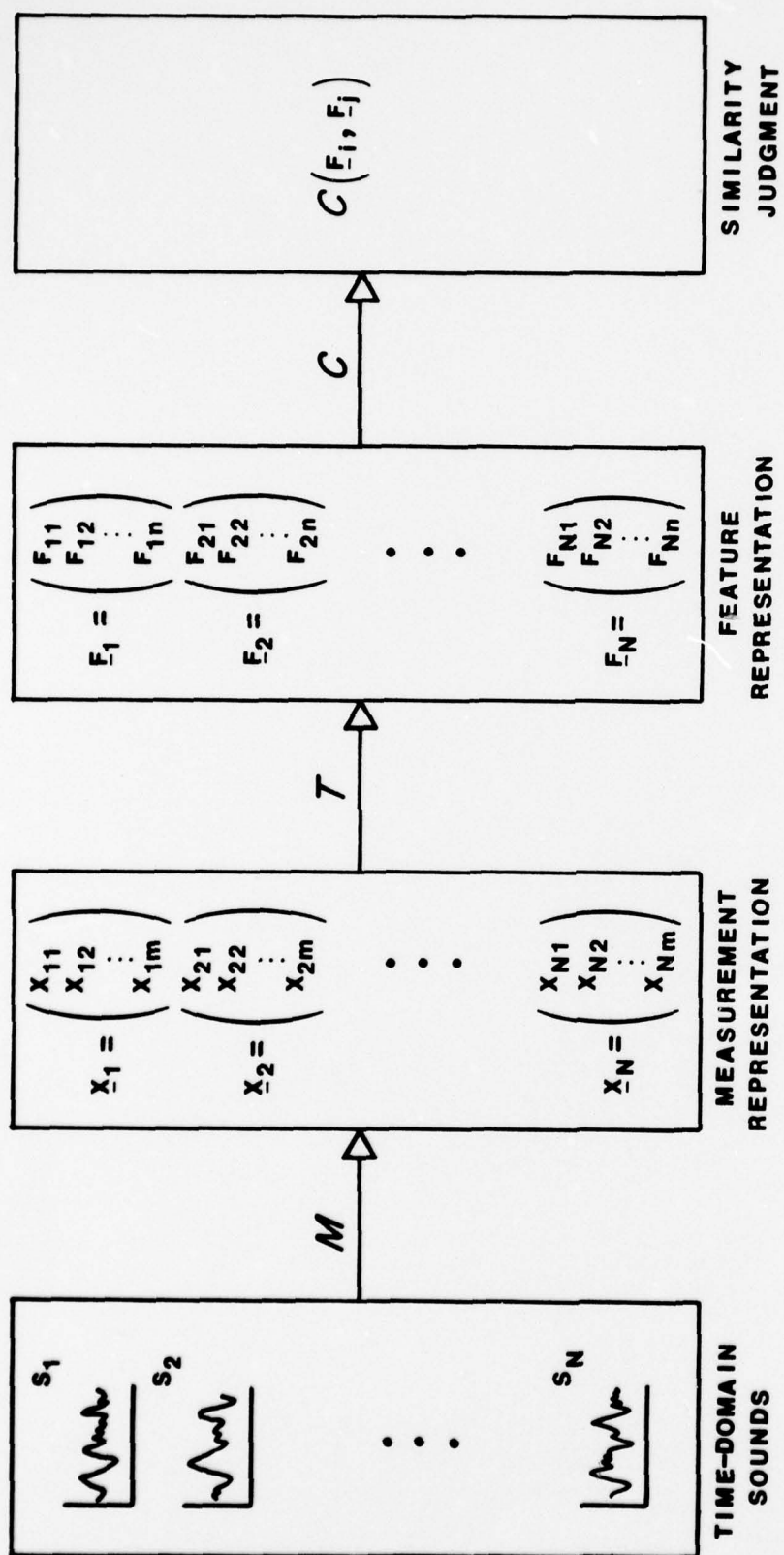TIME-DOMAIN SOUNDS

$S_1$ $S_2$ $\cdots$ $S_N$

Figure 1. Preliminary three-stage model of the aural comparison process.

$\underline{x}_i' = (x_{i1}, x_{i2}, \ldots, x_{im})$.   After this, a second transformation, $T$, occurs that extracts a set of comparison features from the measurement vectors. In our model we assume that the outcome of this transformation is a column vector of n feature values for each stimulus. That is, $\underline{f}_i = T(\underline{x}_i)$, where $\underline{f}_i' = (f_{i1}, f_{i2}, \ldots, f_{in})$ with $n \leq m$. Once the feature information is available, the listener compares the stimuli to determine a similarity judgment, $C(\underline{f}_i, \underline{f}_j)$.

The heart of the feature selection problem involves specifying the transformation $T$. Following Howard and Ballas (1978), we have argued that this transformation reflects the outcome of a structural analysis of the stimulus set, much like a principal components analysis. This assumption specifies four important properties of the transformation. First, the transformation is linear. Since the features represent new dimensions in the measurement space, the transformation must project each stimulus in the measurement space onto the new dimensions. The feature values, $\underline{f}_i$, for stimulus $S_i$ are therefore weighted linear combinations of the original measurements, $\underline{x}_i$. In matrix notation, each vector of feature values is the product of a measurement vector and an n by m matrix of weights or coefficients, $\underline{T}$, $\underline{f}_i = \underline{T}\,\underline{x}_i$, or

$$\begin{pmatrix} f_{i1} \\ f_{i2} \\ \cdot \\ \cdot \\ \cdot \\ f_{in} \end{pmatrix} = \begin{pmatrix} t_{11} & t_{12} & \cdots & t_{1m} \\ t_{21} & t_{22} & \cdots & t_{2m} \\ \cdot \\ \cdot \\ \cdot \\ t_{n1} & t_{n2} & \cdots & t_{nm} \end{pmatrix} \begin{pmatrix} x_{i1} \\ x_{i2} \\ \cdot \\ \cdot \\ \cdot \\ x_{im} \end{pmatrix}.$$

In this view, the jth feature coordinate for stimulus $S_i$, $f_{ij}$, is determined by the inner product of the jth row vector of $\underline{T}$ and the measurement vector for that stimulus, $f_{ij} = \sum_{k=1}^{m} t_{jk} \cdot x_{ik}$.

Second, the transformation should project stimuli from the m-dimensional measurement space onto the n-dimensional feature space while preserving as much of the original information as possible. This is achieved by selecting transformation coefficients, $\underline{T}$, such that the variance of stimulus projections onto each dimension is maximal.

Third, the transformation coefficient vector for each feature (i.e., each row in the $\underline{T}$ matrix) should be of unit length. This restriction is required to avoid trivially satisfying the second condition by selecting arbitrarily large coefficients.

Fourth, the transformation coefficient vectors should be mutually orthogonal. Since the primary function of the feature transformation is to eliminate redundancy in the measurement representations, it is obviously desirable that the features carry as little overlapping information as possible. Together with the third condition, this specifies that the vectors of projection coefficients be orthonormal, i.e., orthogonal and of unit length.

Transformations having these properties are frequently encountered in the theoretical pattern recognition literature, and represent a particular instance of the discrete Karhunen-Loève expansion (Meisel, 1972; Young & Calvert, 1974). Fortunately, the desired transformation coefficients are readily

obtained by decomposing the symmetric m by m covariance matrix of stimulus measurements (in our case the 1/3-octave band levels) using standard techniques. The normalized eigenvectors resulting from this decomposition provide the transformation coefficients, and the corresponding eigenvalues indicate the relative importance of each eigenvector. An optimal n-dimensional feature space may then be determined by selecting the n eigenvectors having the largest eigenvalues.

More specifically, to decompose the covariance matrix we need to solve the well-known eigenvalue problem

$$\underline{K}\,\underline{e}_i = \sigma_i^2\,\underline{e}_i \quad i = 1, 2, \ldots, m.$$

where $\underline{K}$ represents the covariance matrix, $\{\underline{e}_i\}$ represents a set of m orthogonal solution vectors, called eigenvectors, and $\{\sigma_i^2\}$ are a set of m associated scalars called eigenvalues (Green & Carroll, 1976). In the present context, the eigenvectors indicate the new dimensions in the feature space and the ith eigenvalue reflects the variability of stimulus projections onto the ith feature dimension. Although m eigenvectors exist for an m by m covariance matrix, a more efficient stimulus representation can be obtained by discarding the eigenvectors that account for relatively little of the stimulus variability. To the extent that redundancy exists in the original measurements, the information in the stimulus can be adequately portrayed with fewer dimensions in the feature space than in the measurement space (i.e., n < m in the notation developed above). Once we have selected the n eigenvectors, these values determine the coefficients in the transformation

matrix $\underline{T}$, i.e.,

$$\underline{T} = \begin{pmatrix} \underline{e}'_1 \\ \underline{e}'_2 \\ . \\ . \\ . \\ \underline{e}'_n \end{pmatrix} = \begin{pmatrix} \underline{t}'_1 \\ \underline{t}'_2 \\ . \\ . \\ . \\ \underline{t}'_n \end{pmatrix} .$$

## Rationale

In the present paper we will examine the above model as a characterization of the feature selection process for human listeners in a timbre comparison task. Since it is well known that the shape of the amplitude spectrum is the primary physical correlate of timbre (Plomp, 1976), any model that describes the feature selection process must account for its effects on the psychological feature representation. Because we are primarily interested in the transformations involved in timbre perception, sixteen complex, steady-state sounds that differ in spectral shape will be used in the present experiment. The sounds were synthesized by combining individual sinusoidal components at 1/3-octave intervals. These intervals were selected since it is generally accepted that the ear resembles a set of 1/3-octave filters in its frequency resolving power (Plomp, 1976). The amplitude spectra were shaped by combining the components at various amplitudes. All sixteen sounds had two spectral peaks or formants of differing peak ratio and distinctiveness.

The set of sixteen complex sounds will be presented to listeners for pairwise similarity judgments. A measurement vector $(\underline{x}_i)$ will be obtained for each sound by

amplitude-weighting the 1/3-octave band levels using Steven's loudness function (Stevens, 1972). These loudness-adjusted spectra will be analyzed according to the procedures outlined above to determine an optimal structure-preserving feature transformation. The feature representation predicted by this theoretical analysis will be compared to the subjective feature representation observed in the experiment to test the adequacy of the model.

The feature representation actually used by the listeners will be estimated by submitting the observed similarity matrices to a nonmetric multidimensional scaling analysis. In particular, the ALSCAL program (Takane, Young & de Leeuw, 1977) will be used to decompose the data into an n-dimensional metric space in which each stimulus is represented as a single point or vector. The dimensions revealed in this analysis will be taken to reflect those features that the listeners employed to compare the sounds.

## Method

### Subjects

Six undergraduate student volunteers (5 males and 1 female) were paid an average of $3.00 per hour for their participation. All students had some musical background; however, none had taken formal training in the last three years. The volunteers reported no history of hearing disorders.

### Apparatus

All experimental events were controlled by a Digital Equipment Corporation PDP-8/e computer. Statistical analyses

were carried out on the Catholic University's DECSystem-10 computer using the IMSL statistical library, and the ALSCAL multidimensional scaling program (Takane et al., 1977).

Listeners were isolated in a sound-attenuated booth during the experiment. A video display was used to present verbal feedback and instructions, and listeners entered their responses on a solid-state keyboard. A 12-bit digital-to-analog converter (Digital Equipment Corporation AA50) was used to output the complex auditory waveforms at a sampling rate of 10 kHz. Synthesized waveforms were low-pass filtered (Krohn-Hite Model 3550) with an upper cutoff frequency of 4 kHz to remove aliasing frequencies. The sounds were passed through a programmable attenuator (Texscan PA-50) before being presented over matched headphones (Telephonics TDH-49, MX41/AR cushions).

Stimuli

Sixteen complex steady-state sounds were constructed digitally by adding together 22 individual sinusoidal components. As indicated above, these components were spaced at 1/3-octave intervals between 20 and 2500 Hz. Two parameters, peak ratio and peak smear were varied to produce amplitude spectra of different shapes. The resulting spectra had maxima at 500 and 1000 Hz with peak amplitude ratios of 1.00, .90, .80, or .70 on a logarithmic scale. The amplitudes of the remaining frequency components were determined by Gaussian distributions centered at the two peak frequencies. Peak smear was manipulated by varying the standard deviation of the distributions (50, 100, 200, or 400 Hz). Thus, the spectra had

two distinct peaks with small standard deviations, but appeared
smeared with large standard deviations. It should be noted that
the two parameters are not orthogonal since either a low peak
ratio or a large standard deviation would produce a more uniform
spectrum. The four extreme spectra produced by the combination
of these two dimensions are displayed in Figure 2, and the
physical parameters for each stimulus are presented in Table 1.

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Insert Figure 2 and Table 1 here

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The stimuli were equated subjectively for loudness by a
preliminary group of listeners who did not participate in the
experiment. The loudness-equated sounds were presented at
levels of between 76 and 78 dB SPL.

Procedure

Participants were seated in the sound-attenuated booth and
were given typewritten instructions. After the listeners
understood the instructions, the complex set of sixteen sounds
were presented four times in order to familiarize the person
with the sounds they were to compare. The listener was
instructed that he or she was to compare the stimuli, and assign
a rating of "5" if the two sounds were very similar or a rating
of "1" if the sounds were very dissimilar. The ratings between
1 and 5 were to be used for pairs of intermediate similarity.
After the initial familiarization period, the listeners
participated in the comparison task for three days in one-hour
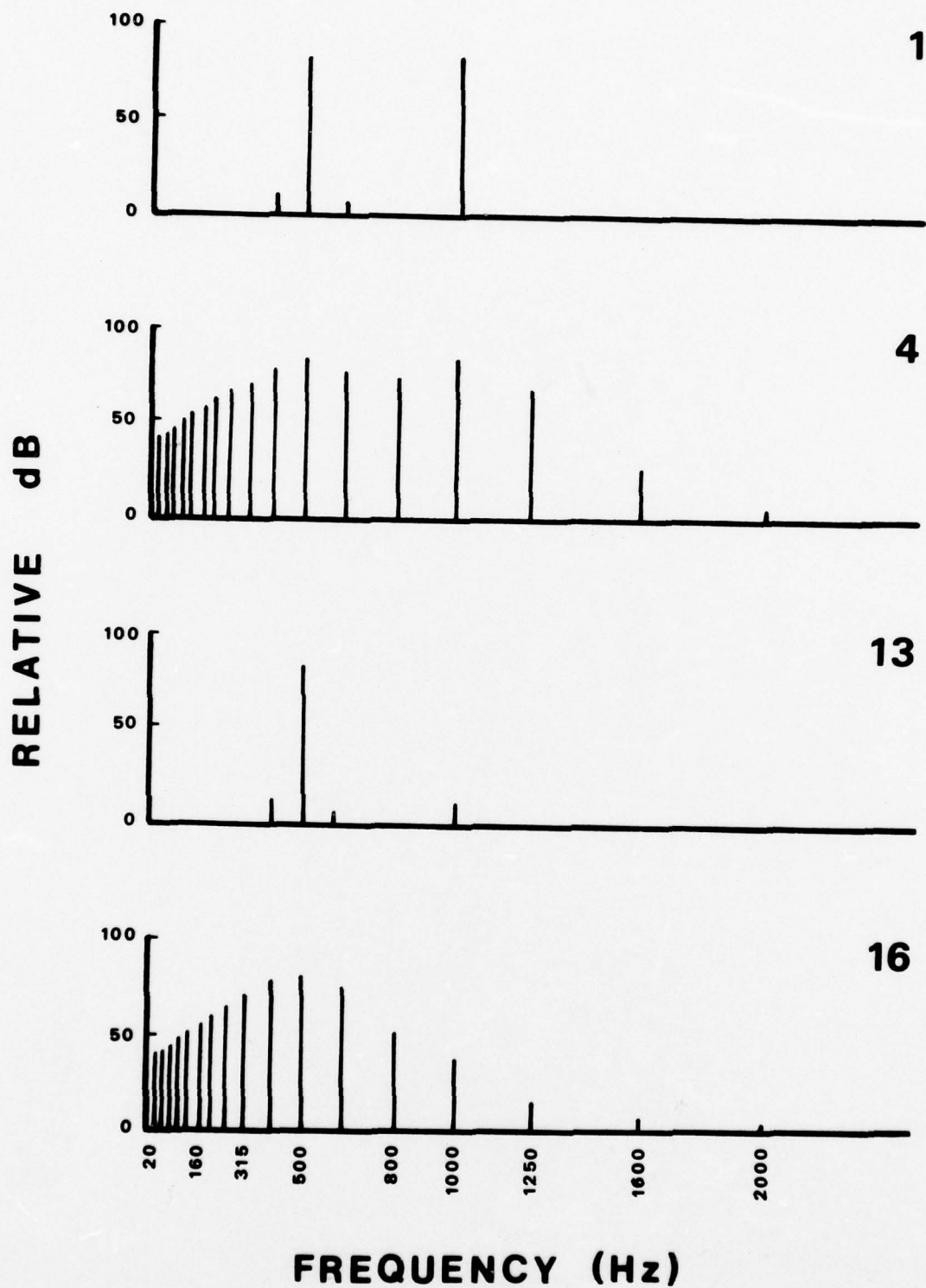sessions. At the end of the third day, a brief sound-sorting

Figure 2. Four extreme spectra (sounds 1, 4, 13, and 16) produced by the combination of the peak ratio and peak smear parameters.

Table 1

Physical Parameter Values Used to Generate Each of the Sixteen Test Sounds.
Peak Ratio Refers to the Amplitude in dB of the 1000 Hz Peak Relative
to the 500 Hz Peak.  Peak Smear is Expressed in Standard Deviation
Units (Hz).

| Sound | Peak Ratio | Peak Smear |
|-------|------------|------------|
| 1 | 1.00 | 50 |
| 2 | 1.00 | 100 |
| 3 | 1.00 | 200 |
| 4 | 1.00 | 400 |
| 5 | .90 | 50 |
| 6 | .90 | 100 |
| 7 | .90 | 200 |
| 8 | .90 | 400 |
| 9 | .80 | 50 |
| 10 | .80 | 100 |
| 11 | .80 | 200 |
| 12 | .80 | 400 |
| 13 | .70 | 50 |
| 14 | .70 | 100 |
| 15 | .70 | 200 |
| 16 | .70 | 400 |

task was given in which the listener had to order the sounds from lowest to highest pitch by making pairwise judgments. The participants were not informed of the pitch-sorting task until after the third scaling session. The pitch-sorting task was included to assess the possible role of pitch in the similarity data.

Each trial in the similarity rating task began when the word LISTEN appeared on the video display. After a brief delay, successive three second samples of the comparison sounds were presented with a one second interstimulus interval. After the second stimulus was presented, the words RATE SIMILARITY were displayed. Listeners were allowed unlimited time to make their response; however, most responded within four seconds. After the listener reponded, the display was cleared and the next trial began. Each of the 120 possible stimulus pairs were presented twice, counterbalanced for order of presentation. This procedure was repeated on each of the three successive days.

At the end of the third day, listeners participated in the pitch-sorting task. Before beginning, each of the sixteen sounds was played to review the entire set. On each rating trial, the participant saw the word LISTEN followed by a stimulus pair, and then the words WHICH SOUND WAS LOWEST IN PITCH (I.E., MORE BASS SOUNDING)?, were displayed. The listener then pressed "1" if the first sound was lower than the second, or "2" if the second was lower than the first. The listener could repeat the trial by pressing a key marked "S." A

bubble-sort algorithm was employed to sort the sounds using the pairwise pitch ratings. After the sort was complete, the listener heard all of the sounds in the pitch ordering that he had determined. If the listener was not satisfied with this ordering, the above task could be repeated. However, all listeners required only one pass to achieve a satisfactory sorting. Sound pairs were presented in a different random order for each listener.

## Results and Discussion

### Theoretical Analysis

A predicted feature representation was obtained by applying the model to the 22-element measurement vectors ($\underline{x}_i$) for the sixteen sounds. As indicated in the introduction, the predicted features are simply principal component axes obtained in an eigen-analysis of the measurement covariance matrix. The variance acconted for by each axis or feature is given by the corresponding eigenvalue. In the present case, the first two principal components accounted for 91% of the overall stimulus variability (74% and 17% for the first and second principal components, respectively). Since the third principal component accounted for less than 6% of the overall variance, it was not considered further. This analysis indicates that listeners need only use two comparison features to account for most of the variability in the present stimuli.

The normalized transformation coefficients obtained in this analysis are displayed in Table 2. As indicated in the introduction, the feature projections for any stimulus are

obtained    from    the    matrix    equation,    $\underline{f}_i = \underline{T}\,\underline{x}_i$,    where    the

transformation matrix is given by the coefficients in   Table   2,

$\underline{T} = \begin{pmatrix} \underline{t}'_1 \\ \underline{t}'_2 \end{pmatrix}$.    The   left   half   of Figure 3 displays a plot of the

sixteen stimuli in the predicted two-dimensional feature space.

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Insert Figure 3 and Table 2 here

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It is obvious from an examination  of  Figure  3  that  the

first   principal   component  (Dimension 1) is related to the peak

smear parameter used to generate the  stimuli.    Stimuli  having

the least smear (1, 5, 9, 13) appear at the far right along this

dimension, whereas stimuli having the greatest smear (4, 8,  12,

16)  appear  on  the extreme left.  It is also evident, however,

that stimuli having the same peak smear do  not  have  identical

Dimension  1  coordinates.  For example, sounds 3, 7, 11, and 15

were all synthesized with a standard deviation of  200  Hz,  but

have  differing  coordinates  along this dimension.  It appears,

then, that although Dimension 1 is determined primarily by  peak

smear, it also depends on the peak ratio parameter.

A more complete description of this predicted  feature  may

be  obtained  by examining the $\underline{t}_1$ coefficient vector in Table 2.

Since the Dimension 1 projection for any stimulus  is  simply  a

weighted  linear  combination of its 22 band-level measurements,

the  coefficients  indicate  the  relative  importance  of  each

individual band level.  For Dimension 1, the two frequency bands

lying between the 500 and 1000 Hz peaks, 630 and  800  Hz,  have

the largest coefficients.  This is generally consistent with our
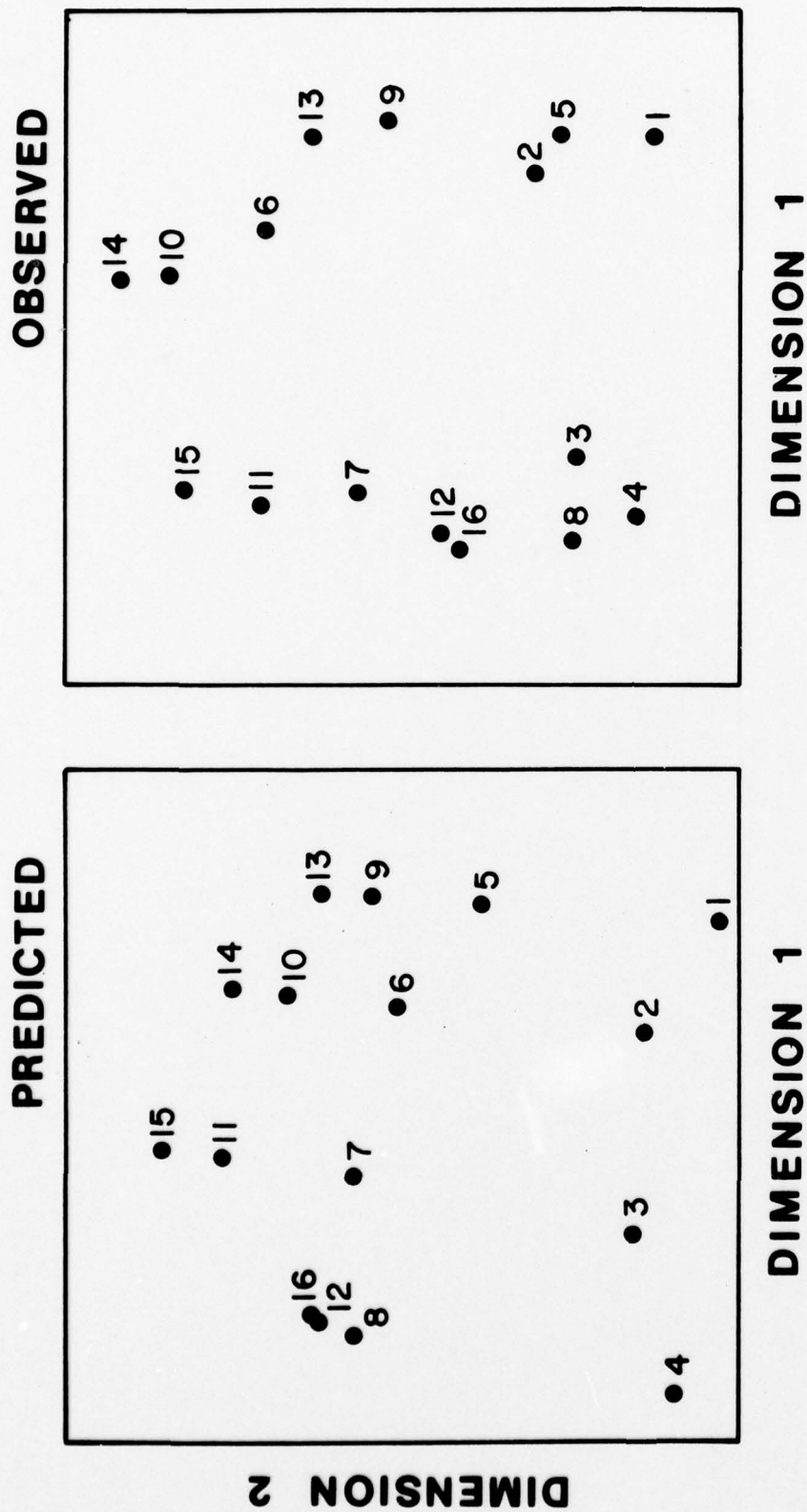
Figure 3. Plots of the predicted (left half) and observed (right half) two-dimensional feature spaces for sixteen complex steady-state sounds.

Table 2

Normalized Transformation Coefficients (x $10^5$) for Each Frequency Component

Obtained in a Theoretical Analysis of the Sixteen Sounds. The Two Co-

efficient Vectors, $\underline{t}_1$ and $\underline{t}_2$ Form the Predicted Transform Matrix T.[a]

| Component | Frequency (Hz) | $\underline{t}_1$ | $\underline{t}_2$ |
|-----------|----------------|-------------------|-------------------|
| 1 | 20 | -38 | -1 |
| 2 | 25 | -39 | -1 |
| 3 | 31.5 | -40 | -1 |
| 4 | 40 | -41 | 0 |
| 5 | 50 | -42 | 0 |
| 6 | 63 | -44 | 1 |
| 7 | 80 | -46 | 2 |
| 8 | 100 | -55 | 5 |
| 9 | 125 | -75 | 10 |
| 10 | 160 | -98 | 21 |
| 11 | 200 | -129 | 39 |
| 12 | 250 | -144 | 63 |
| 13 | 315 | -174 | 114 |
| 14 | 400 | -206 | 211 |
| 15 | 500 | -- | -- |
| 16 | 630 | -236 | 211 |
| 17 | 800 | -218 | 83 |
| 18 | 1000 | -66 | -998 |
| 19 | 1250 | -136 | -313 |
| 20 | 1600 | -44 | -93 |
| 21 | 2000 | -8 | -17 |
| 22 | 2500 | 0 | 0 |

[a] Component amplitudes were equated at the 500 Hz peak, hence, zero coefficients were observed.

observation that Dimension 1 is most closely related to the peak
smear parameter. However, the amplitude of components lying
between the two peaks will be determined by both peak ratio and
peak smear. These values may be increased by either (1)
increasing the smear, as in moving from sound 1 to sound 4, or
(2) increasing the peak ratio, as in moving from sound 15 to
sound 3. In summary, the model predicts that listeners will
focus on the intensity of components between the two peaks as a
primary comparison feature. It is interesting to note in this
context that a similar "peak distinctiveness" perceptual feature
was described by Howard (1977) in an earlier psychophysical
investigation of complex sounds.

When the second dimension is considered, a similar picture
emerges. Examination of Figure 3 clearly indicates that the
stimulus coordinates along this dimension are determined by an
interaction of the peak ratio and peak smear parameters.
Although the peak ratio rank ordering is maintained within
groups of four stimuli, the absolute Dimension 2 coordinate
depends on peak smear as well. As with Dimension 1, a clearer
understanding of this feature may be obtained by examining the
$t_2$ coefficient vector in Table 2. It is interesting that
frequencies below 400 Hz contribute very little to this feature
value. In contrast, the bands adjacent to the 500 Hz peak, 400
and 630 Hz have large positive coefficients, and the 1000 and
1250 Hz bands have very large negative weights. When these
coefficients are applied to transform the 1/3-octave spectra for
our sounds, a "relative pitch" dimension emerges. In

particular, sounds having relatively greater high frequency
energy (i.e., 1000 and 1250 Hz region) will produce large
negative coordinates for this feature. For example, since sound
5 has a lower peak ratio than sound 1, it is clear that it will
have relatively less energy in the high frequency region. When
sound 2 is compared to sound 1, however, we must consider the
role of peak smear. In this case, the 100 Hz standard deviation
used to smear the peaks in sound 2 effectively increases the low
frequency energy relative to the high frequency energy. This
occurs because of the wider 1/3-octave intervals in the high
frequency region. In contrast, when sound 4 is compared to
sound 2, the broader peak smearing used for sound 4 (400 Hz
standard deviation) also increases the amplitude of the more
heavily weighted 1250 Hz component. The net result is that the
Dimension 2 coordinate for sound 4 is somewhat more negative
than that for sound 2. Subjectively, we can say that listeners
are expected to compare the overall pitch of the stimuli within
the four-stimulus clusters along Dimension 1. The expected
interaction of peak smear and peak ratio is clearly evident in
the inverted "U" distribution of stimuli in the predicted
feature space.

To summarize, the feature selection model predicts that
listeners will need only two comparison features to adequately
peform the similarity judgment task for these stimuli. More
specifically, we expect the intensity of inter-peak components
or peak distinctiveness to be particularly important (Dimension
1). The second, but less important feature should reflect the

relative amount of high versus low frequency energy in the
sounds.

Peceptual Analysis

A full 16 by 16 matrix of similarity judgments was obtained
from each listener on each of the three sessions. The first
session was viewed as practice, and these data were not
considered further. Data were summed across the remaining two
sessions to yield a single proximity matrix for each listener.
These data were checked for consistency by computing a Pearson
product-moment correlation between the upper and lower halves of
each matrix. The average correlaion was .70, with five of the
six listeners showing a correlation of .64 or better. This was
taken to indicate that the listener's similarity judgments were
sufficiently stable to justify further analysis.

The summed matrix for each individual was submitted to a
nonmetric individual differences ALSCAL analysis. The selected
nonmetric scaling model required that we only assume ordinal
level measurement in the initial subjective proximity matrices.
In addition, the individual differences model provides a
saliency vector for each listener that indicates the relative
importance of each dimension for that person. The latter
property will enable us to assess individual listener
consistency.

The two-dimensional ALSCAL solution provided an adequate
representation of the subjective similarity data. Although the
observed stress (18.6%) was only in the "fair" range according
to Kruskal (1964), the addition of a third dimension resulted in

little improvement in either stress (5%) or intepretability.   In
addition, Young (1970) has pointed out that for proximity data
containing any sampling error, stress tends to increase with the
number of data points.   This occurs despite the fact that the
scaling solution may actually recover most of the underlying
metric information.   The stimulus space obtained in our scaling
analysis is displayed in the right half of Figure 3.   These data
will be discussed in terms of the theoretical predictions
outlined above.

The finding that a two-dimensional scaling solution was
adequate suggests that our listeners employed two comparison
features.   This was predicted in our theoretical analysis.   It
was further predicted that the two dimensions would differ
widely in their relative importance.   Theoretically, Dimension 1
accounted for 74% of the stimulus variability and Dimension 2
accounted for only 17% of the variability.   A similar result was
observed in our scaling analysis of the perceptual data.   All
six listeners placed relatively greater emphasis on one
dimension (Dimension 1 in Figure 3) than on the other.

An initial visual comparison of the theoretical and
observed feature spaces in Figure 3 reveals both similarities
and differences.   First, it is apparent that the overall
configuration of stimuli is similar in the two spaces.   In both
cases, the stimuli have an inverted "U" distribution, albeit
more pronounced in the subjective space, and the stimulus
projections onto the two axes are generally comparable.   The
Pearson product-moment correlations between the corresponding

coordinates in the two spaces are consistent with this observation ($r$ = .94, $t$(14) = 9.91, $p$ < .01, and $r$ = .82, $t$(14) = 5.46, $p$ < .01 for Dimensions 1 and 2, respectively). The actual theoretical and observed coordinates for both dimensions are presented in Table 3.

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Insert Table 3 here

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We may conclude, therefore, that the feature selection model outlined above successfully predicted the signal attributes that listeners would use to compare the sounds.

However, despite this overall consistency, a number of important differences exist that deserve further comment. With regard to Dimension 1, it is obvious in Figure 3 that listeners did not clearly distinguish the four stimulus clusters predicted by the model. Rather, the listeners tended to dichotomize stimuli along this dimension, maintaining a large peceptual difference between the low peak smear stimuli (50 and 100 Hz standard deviation) and the high peak smear stimuli (200 and 400 Hz standard deviation). It is interesting to note, however, that the predicted between-cluster rank orderings are observed in all cases. Mean Dimension 1 projections of 1.28, .64, -.82, and -1.09 were observed for the four expected clusters (1-5-9-13, 2-6-10-14, 3-7-11-15, and 4-8-12-16, respectively), and in no instance did the clusters overlap along this dimension. It appears, then, that our listeners made somewhat cruder stimulus distinctions in the peak distinctiveness feature

## Table 3

### Predicted and Obtained Psychological Coordinates

### for Each of the Sixteen Complex Sounds

| Sound | Predicted Dimensions | | Observed Dimensions | |
|---|---|---|---|---|
| | 1 | 2 | 1 | 2 |
| 1 | 1.11 | -1.87 | 1.24 | -1.46 |
| 2 | .45 | -1.42 | 1.02 | - .78 |
| 3 | - .74 | -1.37 | - .63 | -1.01 |
| 4 | -1.70 | -1.59 | - .99 | -1.36 |
| 5 | 1.20 | - .45 | 1.28 | - .91 |
| 6 | .60 | .03 | .70 | .83 |
| 7 | - .39 | .32 | - .87 | .29 |
| 8 | -1.34 | .30 | -1.13 | - .99 |
| 9 | 1.25 | .20 | 1.34 | .10 |
| 10 | .66 | .70 | .42 | 1.40 |
| 11 | - .30 | 1.09 | - .92 | .88 |
| 12 | -1.25 | .53 | -1.09 | - .22 |
| 13 | 1.27 | .51 | 1.25 | .53 |
| 14 | .70 | 1.02 | .41 | 1.70 |
| 15 | - .26 | 1.44 | - .85 | 1.32 |
| 16 | -1.24 | .55 | -1.18 | - .32 |

than were predicted by the model.

Another discrepancy of interest was observed in Dimension 2. Here, the interaction of the peak ratio and peak smear parameters was stronger than expected theoretically. In particular, the low frequency dominant sounds (10, 14, 11, and 15) were more clearly distinguished from the high frequency dominant sounds than expected. This difference would occur if the listeners gave the lower spectral region (i.e., adjacent to the 500 Hz peak) greater weight than indicated by the predicted transformation coefficients in Table 2. This result would be expected if perceptual masking effects are considered.

To obtain additional information on the subjective properties of this feature, the results of the pitch ranking task were examined. In this task listeners performed a pairwise pitch sorting of the sounds. If Dimension 2 in the scaling solution reflects overall stimulus pitch, then the pitch ranking obtained in the sorting task should correspond to the Dimension 2 coordinate ranking. Since the six listeners produced generally consistent rank orderings (coefficient of concordance $\underline{W}$ = .87, $X^2$(15) = 77.94, p < .001), a rank of summed ranks was determined for each stimulus. Of interest here was the finding that all eight low peak smear stimuli (i.e., generated with 50 or 100 Hz standard deviations) were ranked lower in pitch than the eight high smear stimuli. This is clearly inconsistent with the observed Dimension 2 projections. It is important to note, however, that only the high smear sounds had any significant energy at frequencies beyond 1000 Hz because of the wider

component spacing in this region. Our listeners were sensitive to this high frequency energy, and assigned these sounds appropriately higher pitch rankings. When the low and high smear sounds are considered separately, the within set orderings correspond reasonably well to the Dimension 2 projection ranks in the perceptual feature space as may be seen in Table 4.

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Insert Table 4 here

---------------------

This observation was confirmed by significant Spearman correlations for both sound clusters ($r$ = .98, $p$ < .01 and $r$ = .71, $p$ < .05 for the low and high smear sounds, respectively). This finding is consistent with our theoretical analysis in indicating that Dimension 2 reflects pitch in a relative rather than absolute sense.

## Summary and Conclusions

The perceptual data considered above were generally consistent with the predictions of our feature selection model. The model successfully predicted the two comparison features that the listeners used to generate their pairwise similarity ratings. In addition, it was able to predict the relative importance of these two dimensions. This suggests that our theoretical assumptions about the listener's feature selection criteria were reasonable. The model proposes that listeners peform a structural analysis of the variability in the stimulus set, and select features that enable them to retain as much of this variability as possible while eliminating redundancy.

Table 4

Rank Order of Low Smear and High Smear Sounds Observed in the Pitch Ranking

Task and Multidimensional Scaling Solution (Dimension 2).

| | Low Smear Sounds | | | High Smear Sounds | |
|---|---|---|---|---|---|
| Sound | Pitch Rank | Scaling | Sound | Pitch Rank | Scaling |
| 1 | 1 | 1 | 3 | 2 | 2 |
| 2 | 4 | 3 | 4 | 1 | 1 |
| 5 | 2 | 2 | 7 | 3.5 | 6 |
| 6 | 6 | 6 | 8 | 3.5 | 3 |
| 9 | 3 | 4 | 11 | 5 | 7 |
| 10 | 7 | 7 | 12 | 6 | 5 |
| 13 | 5 | 5 | 15 | 7.5 | 8 |
| 14 | 8 | 8 | 16 | 7.5 | 4 |

Simply put, the listeners were doing exactly what we expected them to do--that is, compare the sounds--in a statistically efficient manner.

This interpretation is consistent with the process-oriented approach to auditory feature selection (Howard & Ballas, 1978). It asserts that the most reasonable questions to ask about timbre peception should address the feature selection process that listeners use rather than the feature detectors that they use. Indeed, it is entirely possible that specific timbre features do not exist in any absolute sense. The invariant and predictable aspect of timbre perception may well involve a set of rules and criteria that specify a flexible feature selection process. It has been our objective here to investigate this possibility.

Although the present model enjoyed some success in predicting the general characteristics of the perceptual feature space, a number of difficulties exist. In particular, we noted that the fine structure or distribution of stimuli within dimensions was not well handled by the model. This short-coming will hopefully be eliminated as we are able to develop a more precise specification of the proposed transformations. At present, for example, we summarize the contribution of the auditory periphery by a loudness-weighted 1/3-octave spectral analysis. Although reasonable as a first approximation, masking and other known peripheral effects must be considered. Similarly, we must clarify the role of attentional bias in the feature selection process, specify an appropriate measurement

space for transient or time-varying signals, and indicate how the proposed structural analysis takes place on a trial-by-trial basis. These and other questions clearly call for additional research.

Finally, it is important to recognize that the present research has a number of important practical implications beyond the theoretical issues discussed above. Once specified, a feature selection model will enable us to predict a priori the features or sources of variation that listeners will use to evaluate complex aural signals. Once the feature structure is known, the confusability of specific stimuli can be anticipated. In a context where this information is important, e.g., in the classification of aural sonar signatures, preprocessors or other performance aids may be introduced to reduce item confusability as required.

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